DYNAMIC MRI WITH COMPRESSED SENSING IMAGING USING TEMPORAL CORRELATIONS

Jim Ji, Tao Lang
Texas A&M University, College Station, Texas 77840, USA
E-Mail: jimji@tamu.edu

ABSTRACT

Compressed Sensing (CS) is a recently emerged technique for reconstructing signals from data sampled under the Nyquist rate. It takes advantage of the signal sparsity in a transformed domain to reconstruct high-resolution signals from reduced data. This paper presents a CS imaging method for dynamic magnetic resonance imaging. Specifically, a difference operator is applied to the temporal data frames to enhance the spatial signal sparsity for CS reconstruction. The new algorithm method was assessed using simulated and in-vivo dynamic imaging data. The result shows that the new method can obtain higher resolution than zero-padded Fourier reconstruction and the Keyhole method, and it results in reduced artifacts and noise than conventional CS reconstruction where no temporal information is used. It also shows that the new CS dynamic imaging method does not suffer substantial signal-to-noise loss.

Index Terms— MRI, compressed sensing, dynamic MRI image reconstruction

1. INTRODUCTION

Dynamic contrast-enhanced (DCE) magnetic resonance imaging (MRI) is an effective noninvasive tumor diagnosis method. In this method, an image sequence, i.e., "movie", is acquired before, during, and after the administration of a magnetic resonance (MR) contrast agent such as Gd-DTPA (Magnevist®, Berlex Laboratories). The quantitative pharmacokinetic analysis of the contrast agent from the image sequence provides useful information about the angiogenesis and metabolism, which can be potentially used to characterize tumors (malignant or benign) and their response to therapy [1].

In collecting the DCE-MRI images, both high spatial and high temporal resolutions are desirable: the former helps to depict the morphology of tumors, while the later is necessary for describing the wash-in and wash-out contrast kinetics. Due to the limited data acquisition speed of MRI, it is often difficult to collect all the necessary k-space data within the desired imaging time using the conventional fast sequences alone, especially in 3D MRI of large fields of view (FOV). For example, using a state-of-the-art MR scanner and fast gradient-echo pulse sequence, acquiring one 3D multiple slice image with 128 in-plane phase encodings takes more than 10 seconds. However, the desired temporal resolution would be less than 4 seconds for tracer kinetics modeling [2] and subsecond for measuring tumor microcirculation [3].

Several fast imaging methods can be used to address this problem such as parallel imaging with multiple-channel receivers [4,5], and data sharing methods (e.g., Keyhole [6] and RIGR (Reduced-encoding Imaging by Generalized-series Reconstruction) [7]). Parallel imaging requires array coils and multiple-channel receivers which may not be available for the object to be imaged, e.g., certain body geometry or small animals. In addition, increased imaging speed of parallel imaging generally comes with a SNR penalty. In data sharing methods, only a reduced set of k-space data is acquired (therefore increasing temporal resolution). In image reconstruction, full k-space datasets are synthesized from the reduced datasets using prior information from a high-resolution reference image acquired before the dynamic process starts. In doing so, both methods assume that the images features in the dynamic images are strongly correlated with those in the reference.

Compressed Sensing (CS) is a recently emerged technique that has been used for fast MRI of brain and angiography [8,9,10]. A salient feature of CS imaging is that if an image has a sparse representation, either in the spatial domain or a transform domain, then it can be recovered from randomly undersampled k-space data using a nonlinear reconstruction scheme. This implies that compressible signals can be reconstructed from a reduced number of data samples, thereby increasing imaging speed, without reference information. A key in CS imaging is the sparsifying transform which maps the original image to a sparse representation.

This paper presents a CS imaging method for dynamic magnetic resonance imaging. Specifically, a difference operator is applied to the successive temporal data frames to enhance the spatial signal sparsity for CS reconstruction. The new algorithm method was assessed using simulated and in-vivo dynamic imaging data. The result shows that the new method can obtain higher resolution than zero-padded Fourier reconstruction and the Keyhole method, and it

results in reduced artifacts and noise than conventional CS reconstruction where no temporal information is used. It also shows that the new CS dynamic imaging method does not suffer substantial signal-to-noise (SNR) loss.

2. METHOD

The basic idea of the new method is to utilize the temporal correlation of the DCE-MRI frames and the CS reconstruction to obtain dynamic images with high spatial and temporal resolution. In the new method, a high-resolution reference image is acquired before or after contrast injection. The dynamic data frames are undersampled using randomly selected phase encodings (with increased density weighting in the central k-space). The reduced sampling can be use either to acquire more image frames per second, or to increase the coverage of the k-space area in each frame to improve spatial resolution.

After data acquisition, the new method reconstructs the dynamic image using the following model:

$$I = I_{ref} + I_{diff} \quad (1)$$

where I_{diff} represents the desirable difference information that can be extracted from the reference image (I_{ref}) and the intermediate image (I) [4]. Conventionally, both high-resolution reference and high-resolution dynamic images are needed to obtain high-resolution difference information. The key idea of this paper is to take advantage of the characteristics of the difference image I_{diff}, which is spatially sparse by nature because similar structures in both the dynamic and reference images will not show up in I_{diff}. To effectively use this idea, Eq. (1) is rewritten as a corresponding k-space signal model

$$d_{diff} = d - d_{ref} \quad (2)$$

Using this model, the CS algorithm is applied to reconstruct I_{diff} directly from the k-space difference signal as described in Eq. (2). Specifically, after acquiring the reduced k-space data sets according to the random pattern required by the CS imaging, the difference data is taken according to Eq. (2). Then the difference image is reconstructed by optimizing the following cost function, similar to the approach presented in [10]:

$$\varepsilon(I_{diff}) = \left\| FI_{diff} - d_{diff} \right\|^2 + \lambda_{L1} \left| WI_{diff} \right|_1 + \lambda_{TV} TV(I_{diff}) \quad (3)$$

where F is the forward Fourier transform matrix, λ_{L1} and λ_{TV} are two regularization parameters. The matrix W represents a sparsifying transform. In this paper, W is derived from a discrete wavelet transform at level 4 using a biorthogonal kernel. The matrix TV takes the total variations of the image based on the second-order derivatives. $|\cdot|_1$ stands taken the L_1 norm.

This reconstruction problem is highly non-linear and there is no analytical solution for Eq. (3). However, the problem is general convex therefore a conjugate gradient method can be used to search for the optimal solution. In this paper, the optimization was performed using the SparseMRI V0.2 program [10].

3. RESULTS

To test the proposed method and characterize its performance, both computer simulations and in-vivo imaging results were performed. In these studies, high-resolution dynamic images were acquired using 128 phase encodings. The semi-random sampling pattern used in the CS imaging was generated using a center-weighted fashion along the phase encoding dimension (vertical), i.e., the central k-space has a relatively larger sampling density than the outer k-space. The actual data used in the CS reconstruction was obtained by retrospective decimation of the high-resolution data according to the sampling pattern. This decimation corresponds to a four time faster imaging time when applied in practice. Reconstructions were evaluated in terms of resolution, SNR, and artifacts. All processing were performed on a PC workstation with 1.86 GHz CPU and 1.25 GB memory.

3.1 Computer simulations

Simulated dynamic "Shepp-Logan" head phantom datasets was generated using the phantom function and Fourier transform in Matlab (Mathworks, Natick, MA). The phantom consists of multiple elliptical features represents anatomical features of various sizes. To simulate the dynamic contrast enhancement, the intensity of the three "dots" in the middle area of the phantom was doubled from the reference image to the dynamic frame. Next, the two 128 by 128 images were Fourier transformed and shifted to simulate the two k-space data with 128 encodings. Subsequently, the k-space data of the dynamic data was subsampled using a center-weighted randomized sampling mask along the vertical dimension. Only 32 encodings of the dynamic image were kept and used in the reconstruction. As described, the reconstruction from the proposed method corresponds to the difference information. For comparison, difference information from three different reconstruction methods were presented: by two zero-padded Fourier transform reconstructions from the central 32 encodings; by Keyhole reconstruction using 32 central phase encodings and the reference data; and by the conventional CS reconstruction reconstructing each images from the 32 random encodings. For the CS reconstructions, the regularization parameters used were experimentally set to $\lambda_{L1} = 0.005$ and $\lambda_{TV} = 0.0002$.

The top row of Figure 1 shows the reconstruction of the

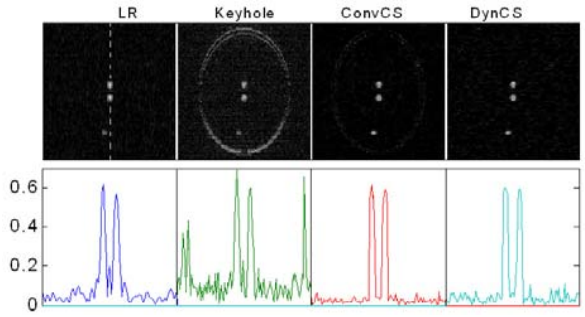

Figure 1. Simulated DCE MRI of a phantom. (Top) Reconstruction from four methods with factor-4 acceleration; (Bottom) One-dimensional profiles corresponding to the location at the dashed vertical line.

dynamic information from (a) low-resolution (LR) by zero-pad Fourier transform; (b) Keyhole; (c) conventional CS reconstruction (ConvCS); and (d) the proposed method (DynCS). The bottom row shows the corresponding 1D profiles at the locations indicated by the white line on the top-left image. Clearly both LR and ConvCS reconstructions contains artifacts along the "head" contour, due to the ringing artifacts. In addition, the LR reconstruction shows reduced resolution, as indicated by the blurring of its 1D rectangular profile. Both ConvCS and DynCS produced less noisy images than the other two methods.

3.2 In-vivo experiment

In addition, the method was tested with *in vivo* dynamic mice tumor data collected on a SISCO 4.7 Tesla system using a rapid T1-weighted gradient echo sequence (matrix 512x128, coronal view, FOV 24cm x 6cm, TR = 63 ms, TE = 4.3 ms, slice thickness = 2 mm, slices = 7, frames = 50, averages = 2). The animal model was a female Sprague Dawley that was anesthetized via intramuscular injection before imaging. The animal was placed in a custom-made bed with a single-channel imaging coil used along with a 1 mM Gd-DTPA imaging fiduciary marker next to the right flank. Each 16 s dynamic acquisition was separated by a 2 s gradient stabilization delay for a total imaging time of 18 s.

Figure 2 shows a typical image of the coronal view dynamic image frame. For better visualization, only the area around the mice's chest (128 x128), inside the dashed white box, will shown later. Figure 3 shows: (a) reference image, (b) dynamic image, and (c) the difference image, all from 128 phase encodings; and the corresponding difference image reconstructed using: (d) Fourier transform (LR), (e) Keyhole, (f) conventional CS without temporal operator, and (g) the proposed method. Images in (d-f) in both figures were reconstructed using 32 encodings, i.e., 25% of the total phase encoding lines. For (e-f), the regularization parameters used were experimentally set to $\lambda_{L1} = 0.005$ and $\lambda_{TV} = 0.0002$. It shows that the CS reconstructions show higher resolution than the Fourier and Keyhole images, as expected. In addition, the proposed method reconstructs images with reduced artifacts and noise than the conventional CS imaging.

To study the effect of the regularization, the two regularization parameters were increased or decreased by a factor of 10. Image reconstructions and the corresponding SNR were evaluated in each combination of the regularization parameters. The SNR of the reconstruction was evaluated using a region of interest (ROI) and a region of region of noise (RON) as indicated by the two black boxes, respectively. The SNR was computed as the ratio between the signal mean inside ROI and the standard deviation inside RON, in the unit of dB. Figure 3 shows the nine reconstructions with different regularization parameters.

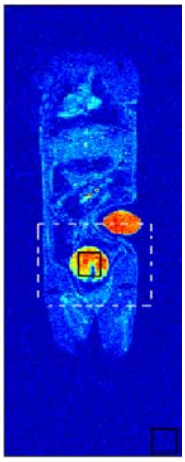

Figure 2. One representative high- resolution image and the localized chest area (dashed white box), region of signal (ROS), and region of noise (RON) (black boxes). The ROS and RON masks will be used to evaluate signal-to-noise ratio of the reconstructed images.

Table 1 shows the corresponding SNR measured from these reconstructions. From these results, it appears that the new method is not very sensitive the selection of the regularization parameters, even the parameters vary by a factor of 1,000. Secondly, larger L1 regularization helps suppress the ringing artifacts. In addition, increasing the TV regularization can reduces noise but leads to noticeable loss of resolution.

Table 1. The SNR of reconstructed images with different regularization parameters (unit: dB).

	λ_{TV}=0.002	0.0002	0.0002
λ_{L1}=0.05	35.9	34.0	32.7
0.005	28.7	26.1	25.9
0.0005	30.1	27.4	26.1

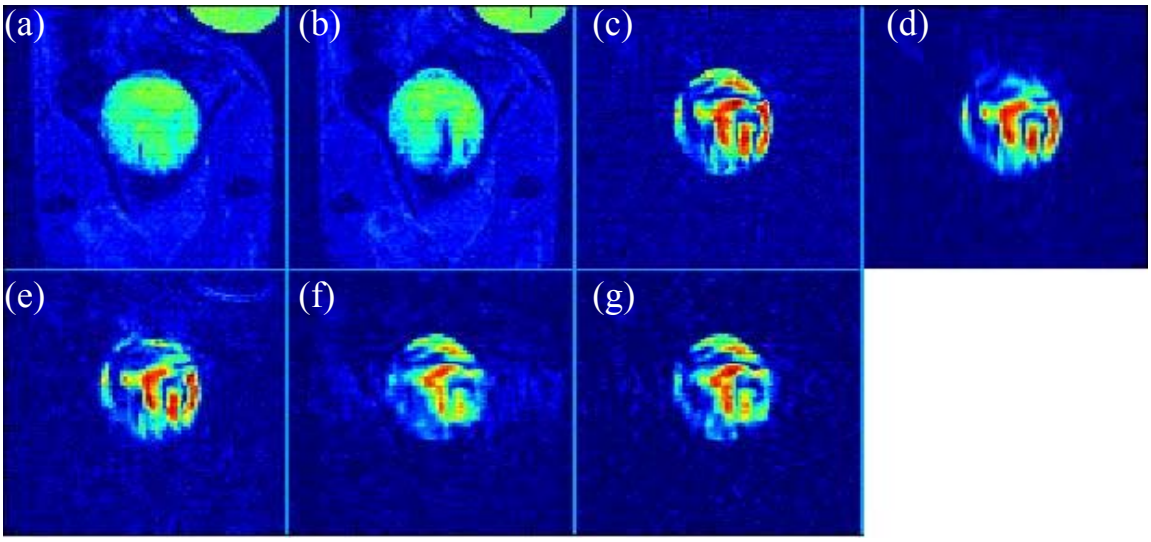

Figure 3. The mice DCE-MRI images (chest area as highlighted in Fig. 2): (a) Reference image; (b) Dynamic frame; and (c) Difference image, from 128 encodings. (d-g) Fourier transform recon, Keyhole recon, the conventional CS recon, and the proposed CS recon, respectively, from 32 encodings.

4. CONCLUSIONS AND DISCUSSION

A CS imaging method for accelerating dynamic contrast enhanced MRI was presented. Computer simulations and in-vivo dynamic imaging results showed that within the same data acquisition time, the new method can obtain higher resolution than zero-padded Fourier reconstruction and the Keyhole method, and it results in reduced artifacts and noise than conventional CS reconstruction. It also shows that the new CS dynamic imaging method does not suffer substantial SNR loss, and the method is not sensitive to the selection of regularization parameters.

Compressed Sensing has proven to be an effective fast MR imaging method. The proposed method took advantage of the temporal redundancy between dynamic image frames to obtain improved image reconstruction quality within this framework. Several technical issues need to be addressed before the method can be fully used for practical applications. First, automatic selection of the two regularization parameter and the wavelet sparsifying transform is required to improve efficiency. Second, we have observed in certain types of DCE-MRI, the method is sensitivity to inter-frame phase variation. A phase correction algorithm should be applied to the complex MRI data in that case. Finally, the current non-linear optimization used for solving the reconstruction is relatively slow as compared to the Fourier transform reconstruction therefore fast algorithm for CS imaging will be of significant practical value.

Acknowledgements: We gratefully acknowledge Drs. Michael Aref and Erik Wiener for providing the *in vivo* data.

References

[1] P. L. Choyke, A. J. Dwyer, and M. V. Knopp, "Invited review functional tumor imaging with dynamic contrast-enhanced magnetic resonance imaging," *J. Magn. Reson. Imag.*, 2003, 17:pp. 509–520.

[2] E. Henderson, B. K. Rutt, and T. Y. Lee, "Temporal sampling requirements for the tracer kinetics modeling of breast disease," *Magn. Reson.Imaging*, 1998, 16(9): pp. 1057–1073.

[3] J. S. Taylor, "MR imaging of tumor microcirculation: Promise for the new millenium," *J. Mag. Reson. Imaging*, 1999, 10: pp. 903–907.

[4] [4] K. P. Pruessmann, M. Weiger, M. B. Scheidegger, and P. Boesiger, "SENSE: Sensitivity encoding for fast MRI," *Magn. Reson. Med.,* 1999, 42: pp. 952-962.

[5] D. K. Sodickson, M. A. Griswold, and P. M. Jakob, "SMASH imaging," *Magn. Reson. Imaging Clin. N. Am.*, 1999, 7: pp. 237-54.

[6] J. J. van Vaals, M. E. Brummer, W. T. Dixon, H. H. Tuithof, H. Engels, R. C. Nelson, B. M. Gerety, J. L. Chezmar, and J. A. den Boer, "Keyhole method for accelerating imaging of contrast agent uptake," *J. Magn.Reson. Imag.*, 1993, 3: pp. 671–675.

[7] Z.-P. Liang and P. C. Lauterbur, "An efficient method for dynamic magnetic resonance imaging," *IEEE Trans. Med. Imaging*, 1993, 13: pp. 677–686.

[8] E. Cand`es, J. Romberg and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information", *IEEE Trans. Infor. Theory*. 2006; 52:489–509.

[9] D. Donoho, "Compressed sensing", *IEEE Trans. Infor. Theory*. 2006; 52:1289–1306.

[10] M. Lustig, D. Donoho and J. Pauly, "Sparse MRI: The Application of Compressed Sensing for Rapid MR Imaging," *Magnetic Resonance in Medicine*, 2007 (in press).